2011

Three essays on real estate finance

Shuang Zhu
Louisiana State University and Agricultural and Mechanical College, szhu4@lsu.edu

THREE ESSAYS ON REAL ESTATE FINANCE

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Interdepartmental Program in Business Administration

(Finance)

by
Shuang Zhu
B.E., Tsinghua University, 1995
M.A., Peking University, 1998
M.S., University of Southern California, 2003
August 2011

Acknowledgments

I have owned a tremendous debt to my committee chair, Prof. R. Kelley Pace, for guiding me through my Ph.D. program, inspiring my interest in research, always trusting and encouraging me, and always supporting me in every aspect of my career. Your dedication and effort can never be thanked enough.

Same credit goes to Prof. Joseph Mason and Prof. Carlos Slawson for the many insightful comments and truly nice support. I would like to thank Prof. Carter Hill for teaching econometrics so well, and setting up an excellent role model. A special thanks to Walter Morales, for the generous donation for data and all the nice help. I would like to thank Prof. Ji-Chai Lin, Prof. Wei-Ling Song, and Prof. Cliff Stephens for sharing their valuable experience.

This dissertation is dedicated to my whole family for their love and support. Mom and dad, thank you for your unconditional love and trust. My husband, Zhongqi, thank you so much for being my "home advisor" and always being with me. Kevin and Kerry, watching you grow up everyday inspired mom to take the challenge and try to be a better person.

Last but not least, I truly appreciate the nice help from my colleagues Fan Chen, Yanhao Fang, Hong Lee, Ping-Wen Sun, and Cihan Uzmanoglu.

Table of Contents

Abstract

This dissertation focuses on the mortgage default behavior and the valuation of distressed properties. Three essays are included.

The first essay uses New Orleans foreclosure data, where each property has three appraisals, to investigate the factors affecting appraisal bias and accuracy, and to estimate the magnitude of appraisal accuracy for distressed properties. Our main finding is that the relation between the client and the appraiser affects valuation bias. Customer employed appraisers tend to give client friendly valuation than their court appointed counterpart. Experienced and licensed appraisers render less biased valuations; while appraisers specializing in lenders tend to give lender friendly valuation. Experienced and licensed appraisers also have more accurate valuation.

The second essay conducts loan-level analysis to investigate the influence of expected foreclosure delay on a borrower's default propensity. The paper includes the *actual* foreclosure times in the analysis which also captures the dynamic nature of foreclosure duration over time. We document the increase in foreclosure duration in recent years. Consistent with the prediction of theory, we find a statistically and economically significant impact of foreclosure delay on borrower default behavior. The results are robust to various specifications such as state fixed effects, different measures for delays, and year fixed effects. For high initial combined loan-to-value ratio mortgages, the increase in delay has stronger impact on default and the effect is consistent across various loan types and borrowers with different credit scores.

Expectations of housing prices play an important role in real estate research. Despite their importance, obtaining a reasonable proxy for such expectations is a challenge. The third essays proposes to use the transaction prices of Case-Shiller housing futures as an alternative "forward-looking" proxy. We compare the performances of four different expectation proxies in explaining borrower mortgage default behavior. The loan level analysis shows that the futures based proxy outperforms other measures by having the highest regression model fit as well as being the only measure that shows a significant negative effect on mortgage default behavior. In addition, the paper shows that futures contain additional information that is not present in the past housing prices.

Chapter 1

Distressed Properties: Valuation Bias and Accuracy

1.1 Introduction

In the current real estate crisis the value of the collateral underlying mortgages has become critical information. Activities such as refinancing, loan modification, and mortgage pricing depend on estimates of value, most commonly supplied by appraisers. Appraisers play an important role in safeguarding the integrity of the housing finance system. Despite their importance, it is difficult to measure their performances, since appraisers usually know the contract price for the property prior to rendering their own estimate of value and this affects their incentives (Chinloy, Cho, and Megbolugbe, 1997).

However, in some cases appraisal accuracy is quantifiable. For example, Dotzour (1988) examines the accuracy of appraisals done for home relocation companies. These appraisals are done prior to the sales contract. Impressively, appraisers with professional designations could display a standard deviation of error of less than three percent. In the context of commercial appraisal, Graff and Young (1999) find that having multiple appraisals allowed quantification of appraisal accuracy. An unbiased appraisal consists of the true value plus random appraisal error. Given multiple unbiased appraisals, one can solve for the magnitude of the appraisal accuracy.

Another situation that results in multiple appraisals is found in the foreclosure process. For example, the foreclosure process in Louisiana often results in three contemporaneous appraisals for each property. Since some characteristics of the clients and the appraisers as well as the neighborhood information of the property are known, this permits investigation of factors that lead to biases in appraisals as well as factors that affect the accuracy of appraisals. The existence of various factors have been discussed in the literature, but obtaining a large number of observations is usually difficult. Much of the valuation literature uses experiment or the survey method to study appraiser behavior. Amidu, Aluko, and Hansz (2008) provide an excellent recent review of much of this valuation literature. In contrast to the small samples often encountered in valuation research, this study of foreclosure data from New Orleans involves $1,532$ properties, each with three appraisals.

A simple unconditional analysis of these data shows a systematic downward bias for lender appraisals and an upward bias for borrower appraisals. However, much of the unconditional bias is explained by various factors. For example, experienced and licensed appraisers (LA) show lower biases. Real estate agents (RS) exhibit an upward bias. Lender specialized appraisers tends to increase biases in favor of the lenders. In addition, court appointed (CA) appraisers exhibit less systematic biases than their customer employed (CE) counterparts. Little systematic bias is associated with various types of demographic and economic variables such as race, income, owner occupied status, and population in the area around the property. In addition, there appear to be little spatial or temporal dependence in the residuals, thus indicating that the appraisers have largely incorporated this information into their valuations.

Also, the analysis examined factors that affect the accuracy of the appraisals (after allowing for the biases). Specifically, appraiser experience and licensing significantly reduce the variance of the appraisal errors. Again, demographic and economic variables pertaining to property and individuals in the area do not affect appraisal accuracy.

The accuracy of valuations on distressed properties could have a material impact on a number of potential policies. First, various proposals (Levitin , 2009) have been made to reduce the principal on distressed properties to their “market value.” This tacitly assumes that accurate estimation of market value is feasible for distressed properties. Second, the Obama Mortgage Plan, more formally termed the 2009 Home Affordable Modification Program, has eligibility requirements with the provision that borrowers must not owe more than 125 percent of the house value (Housing and Urban Development, 2009). Again, the policy depends upon valuation of distressed property. Third, recent changes resulting in the Home Valuation Code of Conduct (Freddie Mac, 2009) may have the effect of changing appraiser characteristics such as experience and compensation which may affect both the bias and variance of valuations. The Home Valuation Code of Conduct promotes the use of Appraisal Management Companies (AMC) which may hire inexperienced appraisers that are not familiar with the area. This could result in an increased incidence of inaccurate appraisals.

In addition, appraisal bias and accuracy naturally affect the valuation and origination of loans. For a seasoned loan a liberal appraisal of the collateral (appraisal greater than value) means that the true loan-to-value ratio is higher and therefore the loan is riskier and worth less than anticipated under a known value of the property. A conservative appraisal (appraisal less than value) means the true loan-to-value ratio is lower and therefore the loan is worth more than anticipated. Given the non-linear nature of loans (when viewed as options), the former effect is more serious than the latter and therefore inaccurate appraisals can have a detrimental effect on portfolio valuation. From a loan origination standpoint, inaccurate appraisals often lead to a breakdown in a potential sale. Consequently, some understanding of the sources of bias and error in appraisals could aid valuation and origination of real estate loans and associated portfolios.

We go into the specific analysis in Section 1.2 and discuss more of the implications of this research in the conclusion.

1.2 New Orleans Foreclosure Appraisals

We examine foreclosure appraisals in New Orleans from 2003 until Katrina in September 2005 for factors underlying appraisal bias and accuracy. In section 1.2.1 we provide the setting and rules pertinent to foreclosure appraisals. In section 3.2.1 we cover the specifics of the foreclosure data. In section 1.2.3 we set forth the specifications and techniques used in investigating bias and accuracy. In section 1.2.4 we look into the factors behind bias and their magnitudes. In section 1.2.5 we derive an estimate of appraiser accuracy. In section 1.2.6 we investigate how appraiser characteristics affect appraisal error.

1.2.1 Institutional Background

Most foreclosure proceedings in Louisiana involve three appraisals of the property. Although the individuals conducting the valuations need not be licensed, each individual takes an oath to make a true and just appraisal of the property.[1] Both the lender and borrower can select their own appraisers. If a party does not select an appraiser, the court will appoint an appraiser to represent that party. In addition, there is a referee who provides another valuation. Although, if the appraisals from the borrower and lender appraisals differ by less than 10 percent, the referee appraisal is simply the average of the lender and borrower appraisals. The minimum sales price (or the starting bid) at the foreclosure auction is 2/3 of the referee's

[1] Since the law uses the term appraisal, but does not require state licensing, we will use the terms appraisal and valuation synonymously.

valuation. The Sheriff's office receives a three percent sales commission. In many cases the appraiser can only examine the exterior of the property.

Borrowers have an incentive to maximize the sales price as it reduces the amount of a possible deficiency judgment. Lenders have a minor incentive to reduce the sales price which will reduce the commission. Almost always, the lender is the successful bidder at the foreclosure auction. Regardless of the price paid at the auction, this will not change the price the lender realizes in a subsequent sale of the property. However, if a lender pays a high price for the property at the foreclosure sale, it reduces the possible deficiency judgment that they could collect. Obtaining the property at a low sales price at the auction may provide a timing option on when to realize gains or losses which could prove beneficial for accounting or tax reasons.

1.2.2 Data

We purchase the data in electronic form from the Orleans Parish Civil Sheriff's office. The files contain observations from 2000 through 2008. Before 2003 the fields for distinguishing between court appointed and customer employed appraisers do not appear in the data. Therefore, we limit our data from 2003 until Katrina hit in September of 2005. The specialization variable and the experience variable are based on two prior years of data. So for the purposes of computing specialization and experience, we also employ data from 2001 and 2002.

The post Katrina period was quite chaotic (Lam et al., 2009). Many of the foreclosed structures were damaged. Also, the voluntary moratoriums on foreclosures meant that many properties stayed unrepaired and subject to the elements for a long period. To avoid confounding many of the Katrina effects with a normal foreclosure market, we stop our data collection at the date of Katrina.

We have some elementary screening of the data. Specifically, we require valid lender, borrower, and referee appraisal amounts for each property. We also exclude low value properties with appraisals of under $\$10,000$ and potential commercial properties with appraisals of over $\$500,000$. Totally 78 observations are deleted because of extreme values and our final sample size is $1,532$.

We measure appraiser experience by the logged number of appraisals performed for foreclosure properties in the last two years by the appraiser and measure specialization in clients by the proportion of appraisals done for lenders in the previous two years. We obtain names for the appraisers and check the Louisiana Real Estate Appraisers Board, Louisiana Real Estate Commission and Louisiana State Bar Association to see if they are licensed appraisers or real estate agents. The binary variables LA and RS equal one if the appraiser is a licensed real estate appraiser or real estate agent, and zero otherwise. Our sample represents 105 individual appraisers. Out of the 105 appraisers, 55 are licensed appraisers, six are real estate agents and 49 do not appear to have any professional designations. The variable CE is also binary which equals to one for customer employed appraisals and zero otherwise. The summary statistics for these variables appear in Table 1.1.

Table 1.1 shows a number of patterns. First, the lender mean appraisal is lower than the referee appraisal, while the borrower appraisal is higher than the referee appraisal. All three appraisals are significantly different from each other at the one percent level for both mean and median pairwise comparisons. Much of these differences are due to various systematic effects examined later in this paper.

Second, lenders tend to employ their own appraisers more often than the borrower (CE as opposed to CA). Lenders employ appraisers around 1/4 of the time while borrowers employ appraisers less than nine percent of the time. Given the lender's motivation favoring lower appraisals, a natural question is why lenders do not always hire their own appraisers. One potential explanation is that the fee charged by the CA appraiser is less than the CE appraiser and the fee should be paid by the lender. Additionally when the appraisal difference between lender and borrower is greater than ten percent, the court will order another appraisal which is used to calculate the starting bid, and this could limit the potential benefit of CE appraisals.[2]

Third, appraisers tend to specialize by client. Lender appraisers work for lender about 65 percent of the time, while borrower appraisers work for lender only around 17 percent of the time and referee appraisers work for lender for less than seven percent of the time. Fourth, a greater portion of licensed appraisers work for the lender than for the borrower and the court. Fifth, lenders and borrowers have more experienced appraisers than the court.

TABLE 1.1. Summary Statistics

	Lender		Borrower		Referee	
Variables	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Appraisal ($1000)	78.6104	60.6711	87.4943	64.2396	84.1740	62.5927
Experience	5.4985	2.0649	5.5747	1.1930	2.3220	2.6170
Specialization	0.6539	0.2949	0.1656	0.2260	0.0699	0.2230
LA	0.5979	0.4905	0.1116	0.3150	0.1090	0.3118
RS	0.0124	0.1107	0.0437	0.2046	0.0868	0.2817
CE	0.2435	0.4293	0.0881	0.2836		

1.2.3 Models

The most straightforward way of measuring appraisal accuracy would be to compare an appraised value with a subsequent transaction price. However, for houses

[2]Also, the data shows that on average the referee appraisal carries a higher value for lender customer employed properties than for lender court appointed properties. This may create a potential selection bias issue. However, we perform a Probit analysis of CE choice using referee appraised value as an explanatory variable. The regression was insignificant. Therefore, we conclude that the potential selection bias does not pose a serious problem.

involved in foreclosure this is difficult since the winning bid is often the minimum set by law (in this case 2/3 of the referee appraisal value). By bidding the minimum amount the lender reduces the small commission paid on foreclosure sales and increases the potential judgment. However, the lender typically has an interest that exceeds the market value and could easily bid this amount. Neither the minimum bid nor the interest the lender has in the property are necessarily equal to market value. For example, Pennington-Cross (2006) argues that the auction price of forclosed property is significantly lower than the market value. Usually, the lender acquires the property and may later repair the property in order to sell it. None of these expenditures are observable. Consequently, measuring appraisal accuracy using foreclosure transaction price or using a subsequent sale of the property by the lender would not prove very informative.

A few equations help motivate an improved procedure. Let $\hat{P}_i^{(o)}$ represent the appraised value of the ith property conducted by the oth party (L for lender, B for borrower, and R for referee). The appraised value is a combination of client characteristics measured by $c_i^{(o)}$, with parameter γ, appraiser characteristics measured by $x_i^{(o)}$, with parameters β, neighborhood characteristics z_i, with parameters $\theta^{(o)}$, disturbances $\varepsilon_i^{(o)}$, and an unobservable variable μ_i. The unobservable variable μ_i captures all the variation across properties not measured by census variables and appraiser and client characteristics in this model. Since property specific characteristics is not included in the observable variables, μ_i is likely to be large and correlated with observable variables.

$$\ln \hat{P}_i^{(o)} = c_i^{(o)}\gamma + x_i^{(o)}\beta + z_i\theta^{(o)} + \mu_i + \varepsilon_i^{(o)} \tag{1.1}$$

$$o = \text{L, B, R}, \quad i = 1 \ldots n \tag{1.2}$$

Because μ_i can be large and correlated with observable variables, we use differencing to eliminate the unobservable or latent values associated with each property. This removes a source of bias (omitted variable bias) and greatly reduces the estimated error of the regression.

$$\ln \hat{P}_i^{(o)} - \ln \hat{P}_i^{(p)} = (c_i^{(o)} - c_i^{(p)})\gamma + (x_i^{(o)} - x_i^{(p)})\beta + z_i(\theta^{(o)} - \theta^{(p)}) + \varepsilon_i^{(o)} - \varepsilon_i^{(p)} \tag{1.3}$$

$$y = C_\delta\gamma + X_\delta\beta + Z\theta_\delta + \varepsilon_\delta \tag{1.4}$$

For unbiased appraisals, each appraisal consists of the underlying μ_i plus a random error component. In this case, all the estimated coefficients of the model would not be significantly different from 0. In addition, the disturbances would not display any dependence over space or time. If the appraisals from the various sources were unbiased, they would all have the same mean for a common group of properties. However, we observe that the means vary across groups from the summary statistics. This suggests that the differences in means across groups may come from incentives and other factors. Given appraisers face varying incentives, we specify some of these incentives as in appraiser characteristics X_δ,

$$\mathrm{X}_\delta = \begin{bmatrix} \mathrm{Experience}_\delta & \mathrm{Specialization}_\delta & \mathrm{LA}_\delta & \mathrm{RS}_\delta \end{bmatrix} \tag{1.5}$$

where X_δ contains the differences in variables as specified in (1.3) so that $\mathrm{Experience}_\delta$ represents the differences between the logs of the number of appraisals performed by the respective appraisers, $\mathrm{Specialization}_\delta$ equals the difference in specialization in lender between the two appraisers, the variables LA_δ and RS_δ take on values of $-1, 0, 1$ as these are differenced binary variables. Client characteristics variable is captured by the variable CE. The differencing variable CE_δ also takes value of $-1, 0, 1$.

First, inexperienced appraisers without much volume of business may need to pay more attention to the client objectives than experienced appraisers, which may lead to more bias. We hypothesize that the coefficient on the variable Experience_δ will be positive for individuals conducting lender appraisals and negative for individuals conducting borrower appraisals versus referee appraisals. For the lender versus borrower regression, we anticipate a positive coefficient for Experience_δ.

Second, appraisers who specialize in performing appraisals for clients may tend to provide appraisals that match the clients' desire. This could either be the outcome of slanting appraisals in favor of the client or the result of client selection of appraisers who tend to render valuations that favor the client. Therefore, we hypothesize that the variable $\text{Specialization}_\delta$ will have negative coefficients.

Third, professional designations represent a form of reputation capital and so, relative to unlicensed individuals, we expect that licensed appraisers would be more likely to provide a higher appraisal to lenders (positive sign) and a lower appraisal to borrowers (negative sign). The same could hold true to a lesser extent for real estate agents. For the lender versus borrower regression, we anticipate positive coefficients for LA_δ and RS_δ.

Fourth, clients pay more to hire their own appraisers and have a motivation to get more favorable valuation. They may put pressure on the appraisers to adjust their valuation. Client selected appraisers may respond to the client pressure by issuing more client favorable valuations than court appointed appraisers. we expect the coefficient of CE_δ is negative for L_B and L_R regressions and positive for B_R regressions.

Appraisals could be affected by neighborhood characteristics as well. We specify these variables in Z,

$$Z = \begin{bmatrix} \text{Land} & \text{Pop} & \text{Black} & \text{Income} & \text{HousePrice} & \text{Owner} & \iota_n \end{bmatrix}$$

where z_i is the ith row of Z, Land is land area, Pop is total population, Black is black population, Income is median household income, HousePrice is the median house price, Owner is units of owner-occupied housing, and ι_n is a n by 1 vector of ones representing the constant term. All of these variables (except ι_n) are logged and are tract level from the 2000 Census.

More populous, higher income, higher priced neighborhoods with a higher amount of owner occupied homes may be easier to value. In this case, the difference between the various appraisals could narrow. Racial aspects of real estate finance have been of interest for many years so we included a variable measuring black population. In addition, we include a variable that gives the land area of the census tract. Given the log specification, this allows interpretation of the other variables in terms of density.

1.2.4 Appraisal Bias

We estimate the specifications in (1.3) using Ordinary Least Squares (OLS). Table 1.2 reports the regression results of the various combinations of appraisal contrasts or differences. Regression one examines the difference between lender appraisals versus the borrower appraisals, regression two examines the lender appraisals versus the referee appraisals and regression three examines the borrower appraisals versus the referee appraisals.

Since lender appraisals on average are lower than both borrower and referee appraisals, the logged appraisal difference as the dependent variable is negative at mean for regression one and two. Thus for regression one and two, variables with negative coefficients increase the bias while variables with positive coefficients reduce the bias. Similarly, since borrower appraisals on average are higher than the referee appraisals, for regression three, variables with negative coefficients decrease the bias while variables with positive coefficients increase the bias. The results show that experienced and licensed appraisers act to significantly counteract bias in favor of the client. For example, the ratio of lender appraisal divided by borrower appraisal rendered by licensed appraisers is on average 2.19% ($e^{0.0217} - 1 = 0.0219$) higher than by the nonlicensed appraisers. Appraisers that specialize in working for lenders tend to provide appraisals that appear slanted in favor of lender. Real estate agents tend to value property higher for both the borrower and the lender. Customer selected appraisers give more favorable valuation to the clients than court appointed appraisers. For example, the ratio of lender appraisal divided by borrower appraisal rendered by customer employed appraisers is on average 4.24% ($e^{-0.0443} - 1 = -0.0424$) lower than by the their court appointed counterparts.

Typically, the census variables are not both statistically significant and large in magnitude. In particular, the racial variable is not statistically significant in any of the regressions. The constant term shows a pattern with lenders showing a more negative intercept than the corresponding borrower regression. However, the differences in the constants are not significantly different. Therefore, the various appraiser characteristic variables seem to have accounted for a large part of the unconditional bias shown in the lender and borrower appraisals. Finally, the residuals do not show spatial or temporal dependence (LeSage and Pace, 2009) which indicates that appraisers largely remove the signal from the data which left only noise. In other words, appraisers (after allowing for various biases) largely incorporate the neighborhood information in valuations.

After controlling for the various biases affecting appraisals, we turn our attention to estimates of appraisal accuracy and the factors affecting accuracy. However, it

TABLE 1.2. Differencing Regressions for Appraisal Bias

	(1) Lender-Borrower	(2) Lender-Referee	(3) Borrower-Referee
Experience_δ	0.0103**	0.0118***	−0.0072***
	(0.0040)	(0.0016)	(0.0009)
$\text{Specialization}_\delta$	−0.0218	−0.0295**	0.0118
	(0.0169)	(0.0136)	(0.0105)
LA_δ	0.0217**	0.0263***	−0.0169**
	(0.0085)	(0.0090)	(0.0077)
RS_δ	0.1197***	0.0622***	0.0238***
	(0.0221)	(0.0126)	(0.0066)
CE_δ	−0.0443***	−0.0322**	0.0025
	(0.0158)	(0.0138)	(0.0100)
Land	−0.0031	−0.0043	−0.0012
	(0.0082)	(0.0060)	(0.0038)
Pop	−0.0620**	−0.0270	0.0128
	(0.0249)	(0.0181)	(0.0115)
Black	0.0048	0.0014	0.0043
	(0.0108)	(0.0078)	(0.0050)
Income	−0.0279	−0.0181	0.0169
	(0.0278)	(0.0201)	(0.0128)
HousePrice	0.0616**	0.0427**	−0.0052
	(0.0257)	(0.0186)	(0.0119)
Owner	0.0452*	0.0211*	−0.0196
	(0.0263)	(0.0118)	(0.0175)
Constant	−0.3024	−0.2654	−0.0448
	(0.2387)	(0.1735)	(0.1109)
N	1532	1532	1532
R^2	0.0908	0.1798	0.0653
RMSE	0.1927	0.1400	0.0893
F	13.7996	30.2856	9.6545

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is difficult by inspection of the differences between the borrower and referee appraisals as well as between the lender and referee appraisals to assess the accuracy of the borrower and lender appraisers since the referee has knowledge of both appraisals before forming their opinion. Although this most likely increases the referee accuracy, it complicates the analysis of the variance.[3] To address this issue, in the following section we examine the random appraisal error from contrasting borrower and lender appraisals. Since borrower and lender appraisals most likely have similar random errors (after filtering out biases), this aids in estimating the underlying accuracy of appraisers.

1.2.5 Appraiser Accuracy

According to equation (1.3), given the borrower and lender appraisals are done independently of each other (which implies statistical independence), this yields (1.6).

$$\sigma^2_{\varepsilon(B)-\varepsilon(L)} = \sigma^2_{\varepsilon(B)} + \sigma^2_{\varepsilon(L)} \tag{1.6}$$

Given the further assumption that the variances of the random errors for lender and borrower appraisers are the same yields (1.7).

$$\sigma_{\varepsilon(B)} = \sigma_{\varepsilon(L)} = (0.5\sigma^2_{\varepsilon(B)-\varepsilon(L)})^{1/2} \tag{1.7}$$

The RMSE for the borrower lender contrast regression (appraisal differences filtered for systematic effects) is an estimate of $\sigma_{\varepsilon(B)-\varepsilon(L)}$. Therefore, from Table 1.2 regression one, we could calculate the standard deviation of the appraisal error as

[3]The referee valuation is thus "anchored" and this can increase error rates in some cases (Diaz and Hansz, 2001). However, given the magnitude of biases in this setting, a referee may serve a very useful role.

$\sqrt{0.5(0.1927)^2} = 13.63$ percent. Translated into mean absolute error (MAE) terms the 13.63 percent standard deviation equals 10.88 percent for a normal random variable. Note, this is just an estimate of the magnitude of the random error and the total error involves both the random error as well as the systematic biases described earlier.

To estimate the appraisal accuracy for unlicensed appraisers, we run lender versus borrower regression using the subsample with both unlicensed lender and borrower appraisers and obtain the RMSE from the regression equal to 0.2622. This translates into the standard deviation of the unlicensed appraisal error as $\sqrt{0.5(0.2622)^2} = 18.54$ percent, or 14.79 percent in MAE. To estimate the accuracy for licensed appraisers, we run the regression requiring licensed appraisers for both lender and borrower and obtain the RMSE equal to 0.1370. This translates into a standard deviation of the licensed appraisal error of $\sqrt{0.5(0.1370)^2} = 0.0969$ or 7.74 percent in MAE.

In contrast, Dotzour (1988) find that designated appraisers working for relocation companies have a MAE of 2.77 percent. This estimate of error contains both systematic and random components. Not surprisingly, the implied accuracy on foreclosure appraisals is far worse than on relocation properties, which are typically well above average in quality.

Given an overall estimate of the random component of appraisal error, this raises the question of which factors materially affect accuracy. We address this in the next section.

1.2.6 Factors Affecting Accuracy

In this section, we investigate how the appraiser characteristics and neighborhood characteristics affect the variances of the residuals from the differencing regressions in Table 1.2. According to equation (1.8), the appraisal variance could be explained by appraiser characteristics and neighborhood characteristics.

$$\hat{\sigma}^2_{i,\varepsilon^{(o)}} = x_i^{(o)}\gamma + z_i\delta^{(o)} + \epsilon_i^{(o)},\ o = \text{L, B} \tag{1.8}$$

However, we could not observe the variance of lender or borrower appraisals. But we could use the residuals e_i from regression one in Table 1.2 as the proxy for $\sigma_{\varepsilon^{(B)}-\varepsilon^{(L)}}$. Substituting equation (1.8) into equation (1.6) yields (1.9) which reduces to the estimation equation (1.10). As shown in equation (1.9), X_a is the average of borrower and lender appraiser characteristics. Thus, Experience_a, Specialization_a, LA_a and RS_a for the residual regression are defined as the average of lender and borrower appraisers' experience, specialization, LA and RS. The estimation results appear in Table 1.3.

$$\ln(e_i^2/2) = 0.5(x_i^{(L)} + x_i^{(B)})\gamma + 0.5z_i(\delta^{(L)} + \delta^{(B)}) + 0.5(\epsilon_i^{(L)} + \epsilon_i^{(B)}) \tag{1.9}$$

$$y = X_a\gamma + Z\delta_a + \epsilon \tag{1.10}$$

Table 1.3 shows that experience and licensing strongly reduce the variance of the residuals, and real estate agents are less accurate. None of the census variables is statistically significant.

To make this more concrete we examine specific cases in Table 1.4 to see how the implied standard deviation and mean absolute error of appraisal error vary by appraiser licensing and experience. We examine licensed and unlicensed appraisers with three levels of experience (5, 50, and 250 appraisals performed for distressed properties in the past two years) in Table 1.4. Census data and the specialization variable are evaluated at their mean values.

TABLE 1.3. Residual Regression for Appraisal Accuracy $y_i = \ln(e_i^2/2)$

	Residual Regression
Experience_a	-0.4744^{***}
	(0.0793)
Specialization_a	0.4132
	(0.4965)
LA_a	-1.1010^{***}
	(0.3031)
RS_a	2.5480^{***}
	(0.5884)
Land	0.0164
	(0.1083)
Pop	−0.2114
	(0.3275)
Black	0.0400
	(0.1422)
Income	0.0945
	(0.3647)
HousePrice	−0.1823
	(0.3386)
Owner	−0.1133
	(0.2144)
Constant	−0.5448
	(3.1512)
N	1532
R^2	0.0970
RMSE	2.5414
F	16.3363

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 1.4. Implied Standard Deviation and Mean Absolute Error of Random Appraisal Error For Varying Appraiser Licensing and Experience

Cases	Licensed Appraiser	Experience	Std. Dev.	MAE
1	No	5	0.2203	0.1757
2	No	50	0.1276	0.1018
3	No	250	0.0871	0.0695
4	Yes	5	0.1270	0.1013
5	Yes	50	0.0736	0.0588
6	Yes	250	0.0502	0.0401

Table 1.4 makes the role of experience and licensing clear. Although the average appraisal has an implied MAE of 10.88 percent, experienced licensed appraisers can perform much better than that. In the best scenario of a very experienced licensed appraiser as in case 6, the appraisal accuracy is 4.01 percent, slightly higher than the relocation appraisers examined by Dotzour (1988) who have a MAE of 2.77 percent. Going to a licensed appraiser who has done 50 appraisals of distressed properties in the last two years raises the MAE to 5.88 percent. In contrast, unlicensed appraisers with almost no experience can have an implied MAE of 17.57 percent as shown in case 1.

The inaccuracy of inexperience appraisers has implications for programs relying on appraisals. Any major program that requires a large number of distressed properties to be revalued in a short time will need to rely on inexperienced appraisers to handle the workload as the number of appraisers that perform a large number of appraisals in this specialized area is limited. However, inexperienced appraisers will likely not perform well and this will pose a problem for programs that assume accurate valuations are possible. Various loan modification programs such as the Home Affordable Modification Program, the practice of "lien stripping" where the principal on a second mortgage is reduced so that the principal on both the first and second mortgages do not exceed the estimated market value (set by appraisals), and refinancing guidelines (such as those in the Home Affordable Modification Program) all tacitly assume that an appraiser can make an accurate determination of market value for a distressed property.

Similarly, attempts to reduce bias in appraisal sometimes may result in lower accuracy. The Home Valuation Code of Conduct promotes the use of Appraisal Management Companies (AMC) which may hire inexperienced appraisers that are not familiar with the area. In effect, an appraiser going into an unfamiliar area is similar to an inexperienced appraiser. This lack of experience in a particular market could result in an increased incidence of inaccurate appraisals. Inaccurate appraisals may cause legitimate transactions to fail and yet not detect fraudulent transactions.

1.3 Conclusion

The relation between the client and the appraiser affects valuation bias. First, whether the appraiser works for the court as opposed to the clients makes a difference. In the regression estimating the biases, the coefficients on variables measuring client characteristics indicating that customer employed appraisers give more client favorable valuations. This implies that client pressure might exist for the valuation process. Second, individuals that specialize in lender exhibit biases in favor of the lender. Third, appraisers with more experience may have less dependence on any client and these appraisers show a reduction in bias in favor of the client. Fourth, licensed individuals may have more reputation capital and thus have incentives to resist client pressures. Licensed appraisers show a reduction in bias in favor of the client. However, real estate agents show an upward bias relative to other individuals in all cases. Many of the same factors affected valuation accuracy as well. In particular, experience and licensing increase accuracy.

We estimate that the magnitude of the random appraisal error (as measured by mean absolute error) is 10.9 percent for these properties, 7.7 percent for licensed appraisers and 14.8 percent for unlicensed appraisers and the total appraisal error (random plus systematic components) would go beyond this level. This greatly exceeds the error found in other settings such as for relocation appraisals. The lack of accuracy has implications for policies that rely upon real estate valuations for principal reduction, purchase, or refinancing. For example, the 2009 Home

Affordable Modification Program (Obama Mortgage Plan) eligibility requirements contain the provision that borrowers must not owe more than 125 percent of the value of home. Given the high error rate in just the random component of appraisal error, many borrowers could either qualify or not qualify based only on appraisal error.

Appraisal bias and accuracy naturally affect the valuation of loans. Adjustments need to be made to models assuming a known value to account for the uncertain value of the collateral. In areas with distressed properties, the accuracy and biases for these appraisals may more closely resemble this foreclosure setting.

Appraisal problems affect both the purchase of housing and the refinancing of loans. Poor appraisals can lead to cancellations of sales, loan denial, and other problems. None of these problems helps the efficiency of the housing market.

Chapter 2

The Influence of Foreclosure Delays on Borrower's Default Behavior

2.1 Introduction

When mortgage borrowers miss their monthly payments for a certain time period, typically after three complete missing payments, lenders may initiate the foreclosure process. The conclusion of the foreclosure process is normally through the foreclosure sale.[1] The duration from the first missing payment date to the end of the foreclosure sale represents the foreclosure delay or foreclosure duration. During this time period, the defaulting borrower can legally stay in the house without making payments and enjoy "free rent."

Recent developments such as the pressure on servicers to modify loans, foreclosure moratoria on the part of states or lenders, state foreclosure mitigation efforts, and foreclosure documentation issues have all contributed to a longer foreclosure period. This raises the question on the sensitivity of default to such foreclosure delays. If default is insensitive to foreclosure delays, increasing the foreclosure period may provide temporary relief for defaulting borrowers and may lead to self cure of default.[2] Alternatively, if default is sensitive to foreclosure delays, increasing the foreclosure period may compound problems in the mortgage market as it increases incentives to default and thus makes default optimal for more borrowers.

From an option pricing perspective, rational borrowers make their decision on default based on the expected value of default. Ambrose et al. (1997) explicitly introduced foreclosure delays in the mortgage pricing model and provided a theo-

[1] Of course, there are other ways of exiting the foreclosure process. For measuring foreclosure delay, we only consider the exit through the foreclosure sale.

[2] On the other hand, longer foreclosure delay may drag borrowers deeper in debt and thus make it hard to come back to current status.

retical basis for the effect of expected delay on the borrower's future default propensity. The theory states that longer expected foreclosure delays tend to increase the probability of default since the "free rent" changes the threshold of whether the default put option is "in the money" or not. However, empirical research has not found support for foreclosure delay affecting the borrower's default decision (e. g. Ghent and Kudlyak, 2010). This apparent discrepancy between theory and empirical evidence, and the ongoing debate on foreclosure mitigation motive us to investigate the issue in deep.

Given the data constraints, previous studies typically include the single-year delays that are based on the non-contested foreclosure process. Although this measure might be useful to gauge the effectiveness of state foreclosure laws, it is not the proper proxy for the borrower's expected foreclosure duration. One reason is that most foreclosure cases include some delays that are beyond the state specified minimum foreclosure times.[3] For example, Pennington-Cross (2010) documented that at individual loan level, many factors could contribute to foreclosure duration. If borrowers base their expectation of future foreclosure duration on their observed delay, a better measure of expected foreclosure duration should be the *actual* foreclosure duration in the recent past. Another reason is, as documented later in the paper, foreclosure durations change over time. Consequently, the single-year static measures fail to capture the dynamic feature of the *actual* foreclosure duration.

Different from previous studies, this paper estimates and includes the *actual* time-varying state-level foreclosure delays to proxy for borrower's expected benefits of "free rent" from default. We document the increase in foreclosure duration in recent years. Using more than four million loan-quarter observations, this

[3]For example, the extra delay may come from the court when the court is overburdened, or from the borrowers when they contest the process, or from third party servicers who have different incentives from the investors or the lenders (Levitin, 2010).

manuscript adopts the Cox proportional model to empirically investigate the impact of expected delays on borrower default propensity. Consistent with the predictions of Ambrose et al. (1997) theoretical model, the results show that borrowers who expect longer foreclosure time have a higher propensity to default.[4] The impact is significant both statistically and economically. The results are robust to state fixed effects, various measures of delay, and year fixed effects. It is not driven by a single state, nor the number of years that the loan performances are tracked. As for the magnitude of the impact, for a three-month increase in delay, the hazard of default on average increases by more than 30 percent, which has the equivalent effect on default propensity as of a 11 percent increase in the current loan-to-value (LTV) ratio or a more than 30 point decrease in Fico score. Higher initial LTV ratio loans are more sensitive to increase in expected delay and the magnitudes of effect tend to be larger.

Currently, many borrowers have negative equity in their properties and foreclosure delays are lengthy. Our study indicates that under such circumstances, borrower's default decisions are more likely to be sensitive to the expected foreclosure duration. From a policy perspective, while helping borrowers who have problems paying their debt by allowing them a "breathing period" seems attractive[5] (Stewart, 2010), this study suggests that it is also important not to make default optimal for more borrowers because of the increased benefit from defaulting.

The rest of the paper proceeds as follows. Section 3.2.1 introduces the data and variables. Section 3.3.1 describes the estimation model. Section 3.3 presents the

[4]Default happens either when borrower has no ability to pay or when he/she chooses not to pay. If default is due to borrower's lack of ability to pay, then foreclosure delays are not supposed to have any impact. On the other hand, our finding that foreclosure delay has an impact on default behavior implies that there might be a significant portion of strategic default.

[5]States that recently enacted foreclosure mitigation laws by giving homeowners "breathing period" include California (90 days), New Jersey (180 days), and Nevada (indefinite time as long as homeowners are requesting loan mediation).

empirical results. Section 3.4 discusses the policy implications of this work and concludes.

2.2 Data, Variables, and Summary Statistics

This section first describes data sources and sample selection, then introduces specifications of other variables, followed by the measurement of foreclosure delay, and discussion of the empirically measured delay.

2.2.1 Data Source and Sample Selection

We use several datasets for our study. The loan-level data comes from Blackbox Logic's BBx.[6] BBx covers over 90 percent of US non-agency residential securitized deals including prime, Alt-A and subprime loans. BBx has detailed mortgage contract information at loan origination and monthly updates of mortgage payment information. The S&P/Case-Shiller Home Price Indices (HPI) are from Bloomberg at the metropolitan (MSA) level. Unemployment data is from the Bureau of Labor Statistics at the MSA level. National average 30 year fixed rate mortgage (FRM) interest rates are from Freddie Mac's national mortgage survey. The zip code level household median income and other demographic variables come from the 2000 Census. Since our data are from privately securitized deals, the results may apply only to this set of mortgages.

We limit the sample to single family, first lien loans with a 30 year contract term in the ten major metropolitan areas that are included in the Case-Shiller 10-city index. We use single family loans since S&P/Case-Shiller HPI is based on single family transactions. The 30 year loan term is the most common loan term and matches the Freddie Mac's national mortgage survey on 30 year loans. We include mortgages originated between January 2005 to December 2007 and track the loan

[6]BBx data is similar to Loan Performance data from CoreLogic. BBx data information is available at www.bbxlogic.com.

performances till December 2009.[7] Since we use strict prior foreclosure delays in the analysis, year 2001 to 2004 data are also used for estimating foreclosure delays. So the time period used in the analysis is from 2001 to 2009. Loans may enter into the dataset as seasoned loans. However seasoned loans may enter into the deals only if they have at most one missing payment in the previous year. This may raise the issue of survival bias. To control for survival bias problem, or the time a loan enters into the database, we require loans to have the first observation of payment information within three months of origination.

2.2.2 Variables

Table 2.1 provides the definitions of variables used in this study. The event of interest is default. According to industry practice, default is defined as the first 90 days delinquency. The status of the loan could be in default, prepaid in full, or censored[8] in any given time period. If the loan is either in default or prepaid, all subsequent observations are dropped out of the sample. One advantage of focusing on 90 days delinquency rather than foreclosure is that default is mainly a borrower's decision while both borrower and servicer play a role in the foreclosure process, which may complicate the analysis. Since our analysis focuses on the influence of foreclosure delay on a borrower's default propensity, defining 90 days delinquency as default is a cleaner setting. Explanatory variables include foreclosure delay, loan characteristics, borrower and neighborhood characteristics, past housing appreciation, lagged unemployment rates, and controls for prepayment risk.

Loan characteristics include: HPI updated LTV ratio, piggyback dummy[9] if the property has junior liens at origination, initial contract rate, documentation status

[7]After 2007, because of the mortgage crisis, very few newly originated loans are added into the dataset.

[8]Loan status other than default or prepaid is considered censored which includes uninformative censoring and current status.

[9]We use piggyback dummy and HPI updated LTV ratio rather than updated combined LTV ratio since after loan origination, we do not have information about the status of the second lien loan.

dummy, investor dummy, purchase dummy,[10] loan amount and loan age. Borrower characteristics include the Fico score. Also included are different loan types as defined in Table 2.1. The performances of non-traditional loans are compared with the fully amortized fixed rate mortgage (FRM) products.

Aspects of the community may affect the borrower's utility of owning the property and change the default threshold (LeSage and Pace, 2009). We include zip code level median household income as a factor to capture the income effect. Other demographic variables included are: population, white population, education, rent, school age children, age over 65, average commute time to work, and percentage of people living in the same house in 1995.

The expected future value of the house affects default decisions (Kau et al., 1993; Foote et al., 2008). We thus include the previous year housing appreciation as the proxy for housing expectation. Past appreciation also reflects the prior year housing market condition. Since the prepayment option must be considered along with the exercise of default option, we include the prepayment penalty dummy and national interest rate difference from loan origination date to the loan activity date to account for the competing risk of prepayment. Lagged unemployment rate is included to help capture local macroeconomic information.

2.2.3 Foreclosure Delay

This section first describes the measurement of foreclosure delay, then discusses the empirically measured delay.

Foreclosure delays are first measured at the individual loan level by the duration from the 30 day delinquency to real estate owned (REO) or property sold at the foreclosure auction. If a borrower makes m payments after being in delinquency

[10] Although it is important to separate cash out refinance and rate refinance, our data does not allow us to reliably do so.

TABLE 2.1. Variable Definitions

Variable	Definition
Default	First 90 days delinquency.
ForeclosureDelay	Lagged state-level foreclosure delays, see discussion in Section 3.2.1.
ExoticARM	Dummy variable, =1 if adjustable rate mortgage with deferred amortization provisions including interest only, negative amortization and/or balloon payment, =0 otherwise.
HybridARM	Dummy variable, =1 if adjustable rate mortgage with fixed initial interest rate, no deferred amortization provisions, =0 otherwise.
RegARM	Dummy variable, =1 if adjustable rate mortgage with no fixed initial interest rate, no deferred amortization provisions, =0 otherwise.
ExoticFRM	Dummy variable, =1 if fixed rate mortgage with deferred amortization provisions including interest only and/or balloon payment, =0 otherwise.
FRM	Dummy variable, =1 if fully amortized fixed rate mortgage, =0 otherwise.
Piggyback	Dummy variable, =1 if the property has junior liens at origination, =0 otherwise.
LTV1	HPI updated loan-to-value ratio.
CLTV	Combined loan-to-value ratio at origination.
FICO	Fair, Isaac and Company credit score of the borrower at origination, scaled by 100.
Interest	Initial contract rate of the mortgage.
FullDoc	Dummy variable, =1 if borrower offers full documentation for loan application, =0 otherwise.
Purchase	Dummy variable, =1 if the loan is for new purchase, =0 otherwise.
Investor	Dummy variable, =1 if the purpose of the use of the house as an investment, =0 otherwise.
LoanAmount	The original loan amount, scaled by 10000.
LoanAge	Loan age in year.
PrepayPenalty	Dummy variable, =1 if the loan has prepayment penalty, =0 otherwise.
RateDiff	Difference of 30 year national average FRM rate between current period and at loan origination.
PastAppr	Past year housing appreciation at MSA level.
Lag Unemployment	Lagged unemployment rate at MSA level.
Income	Log median household income at zip code level.
Rent	Log median rent at zip code level.
Population	Log total population at zip code level.
White	Log white population at zip code level.
Age65	Log population 65+ at zip code level.
Education	% with high school or higher degree at zip code level.
SchoolAgeChildren	% between age 5 and 18 at zip code level.
CommuteTime	Log average commute time to work at zip code level.

status, then m is subtracted from the duration to get the individual loan level foreclosure delays. Effectively, our measure of foreclosure delay represents the period of maximum "free rent" that borrower could obtain from default. Then the individual delays are aggregated at state-year level according to the date of foreclosure termination.[11] We use the lagged state-level foreclosure delays to proxy for the borrower's expected "free rent" from default.[12] Since the foreclosure delays are measured by the duration of delays of the foreclosure cases concluded preceding the year of loan activity date, this strict prior measurement ensures that past delays may affect future default, while future default can not affect past delays. Thus, this proxy avoids the simultaneity issues.

Table 2.2 reports the state-level mean foreclosure delays according to the year of foreclosure concluded. Foreclosure delay shows variations across states as well as over time. For example, for foreclosure cases concluded in year 2008, Virginia had a less than a eight month foreclosure time, while New York required almost 16 months to finish the foreclosure process. The foreclosure periods materially increase over time in most states.[13] For example, New York more than doubled the actual foreclosure period from 2003 to 2008.

Compared to the delay used in the existing literature such as the optimum foreclosure timeline from the National Mortgage Servicer's Reference Directory (USFN, 2004), whose measures assume no extra delay and are based on non-

[11]Another possible way is by aggregating according to the start of the foreclosure. However, this measure might either raise the simultaneity issue or create a selection bias concern. We also tried to estimate the predicted duration through survival models according to the year of foreclosure start while taking care of the censoring issue. However it seems that the predicted value are not very accurate. Although these two measures also have expected sign for delay variable, we decided to stay with our measure.

[12]From transaction cost and benefit perspective, even though we controlled for detailed loan characteristics, borrower characteristics and neighborhood characteristics, which are supposed to absorb large extent of equity consideration, reputation cost, and social capital cost, there is still possibility of omitted cost or benefit. However, only if the omitted cost/benefit are significantly large and highly correlated with foreclosure delay variable, we would not expect the effect of foreclosure delay to change materially.

[13]Foreclosure law itself changed little in our sample period. The reason why the foreclosure times increased significantly over this time period needs future research. Since year 2009 many states changed the foreclosure laws, as a robustness check, we took year 2009 observations out of the sample and the results are similar.

TABLE 2.2. State Mean Foreclosure Delay by Year of Foreclosure Termination

ST	2003	2004	2005	2006	2007	2008
CA	5.02	5.38	7.20	8.68	8.42	9.44
CO	5.94	7.41	7.70	8.20	8.57	9.69
DC	8.06	6.59	7.07	7.12	7.63	8.99
FL	7.37	7.68	8.66	8.49	9.43	12.11
IL	9.23	10.39	10.81	11.96	12.12	13.28
IN	10.10	10.03	11.01	12.43	14.01	14.53
MA	4.95	5.12	7.11	8.71	9.05	11.22
MD	7.16	7.57	8.11	7.32	7.53	9.46
NH	5.09	6.27	5.75	7.13	8.31	9.53
NJ	6.52	5.43	7.20	10.25	12.16	15.11
NV	6.21	5.80	6.20	8.03	8.49	9.33
NY	6.63	7.52	8.82	11.29	12.79	15.97
PA	11.20	10.00	12.67	10.83	12.46	14.37
VA	5.50	5.06	5.12	5.96	6.25	7.52
WI	7.33	11.93	11.88	11.55	12.79	13.88
WV	4.00	10.25	7.67	10.33	7.43	8.27

contested foreclosure actions, ours are the *actual* durations which include extra delays. More important, our measure captures the time variation of foreclosure delays. State foreclosure laws affect foreclosure delays and help explain the variations across states.[14] However, the dynamic nature of delay over time indicates that there are other factors affecting the foreclosure duration as well. Given that, the *actual* foreclosure duration, instead of the state minimum foreclosure duration, might better represent the borrower's expected "free rent" from default.

2.3 Cox Proportional Hazard Model

We use the Cox competing-risk proportional hazard model (Cox, 1972) to investigate the factors that may affect the probability of default. The Cox model can

[14] Judicial procedures require the foreclosure action to go through the court and the complex procedures required by court can lead to longer foreclosure times. Nonjudicial procedures are conducted by private parties and typically are shorter. States may adopt judicial or nonjudicial procedures or both. However, for states that allow both procedures, typically one procedure will dominate the other. State laws also specify various regulated time lines such as when the notice of default should be mailed, the length of time before the arrangement of foreclosure sale, when the notice of sale should be sent, and how long the sale advertisement should be posted. The time frames set by the state law are the minimum foreclosure duration.

take care of right censoring and take time from origination to default into consideration. The basic model specification is as in (2.1), where $h(t)$ is the hazard function of default and $\lambda_0(t)$ is called the baseline hazard function. The explanatory variables in X include both static variables and time-varying variables. Static variables are obtained at or prior to loan origination, while dynamic variables are updated quarterly.

$$h(t, X) = \lambda_0(t) \exp(X\beta) \tag{2.1}$$

The Cox model is a semi-parametric technique that does not require choosing a specific probability distribution of the survival time (baseline hazard function), and is considered a more robust approach. At each time period, the status of a loan could be default, prepaid, or censored which includes uninformative censoring such as leaving the dataset for reasons other than default or prepayment. Prepayment is taken as a competing risk.

State economic, culture and law issues may affect mortgage market behavior (Ghent and Kudlyak, 2010; Pence, 2006; Lin and White, 2001; Berkowitz and Hynes, 1999). These omitted variables may be correlated with included explanatory variables and lead to biased estimation. In order to account for the differences among states, we include the state fixed effect in the hazard model by allowing the baseline hazard to be estimated separately for each state. Since the state fixed effect captures the cross sectional variation between states, our results are driven by the change of foreclosure delays over time. This is a similar approach as Lin and White (2001) and Berkowitz and Hynes (1999) using fixed effects to control for regional differences in their study on how the changes in bankruptcy law affect the mortgage market.

2.4 Empirical Results

This section sets forth the Cox hazard model to study the effects of various factors on borrower's default decision. Section 2.4.1 presents the overall results. Section 2.4.2 focuses on the various robustness check of the impacts of foreclosure delays on default behavior. Section 2.4.3 investigates the sensitivity of default to expected foreclosure duration for different initial combined LTV ratio loans. The event of interest is the first 90 days delinquency, with prepayment as the competing risk. We estimate the reduced form equation. The reported standard errors are clustered by state.

2.4.1 Foreclosure Delays and Future Default

Table 2.3 reports the results of various specifications of the Cox proportional hazard model. Regression one is the result without a delay variable. Regression two to four use the lagged mean state-level delay. Regression three includes the temporal fixed effects. State specific factors regarding deficiency judgments, statutory right of redemption and homestead exemption may also have an effect on the mortgage market. To control for such difference, we include the state fixed effects in regressions four and five. As a robustness check of the proxies for delay expectations, regression five uses smoothed delays by taking the average of the past two years delays since information transfer might take time and also may accumulate over time.

TABLE 2.3. Hazard Model of Default with Different Model Specification

	(1)	(2)	(3)	(4)	(5)
				State FE	
	No Delay	With Delay	Year FE	Mean	Smooth
ForeclosureDelay		0.0749**	0.0618**	0.0940**	0.1013**
		(0.0146)	(0.0180)	(0.0218)	(0.0239)
ExoticARM	0.6443**	0.6613**	0.6581**	0.6346**	0.6340**
	(0.0282)	(0.0256)	(0.0248)	(0.0242)	(0.0248)
HybridARM	0.6554**	0.6449**	0.6525**	0.6216**	0.6209**
	(0.0187)	(0.0165)	(0.0150)	(0.0202)	(0.0204)
ExoticFRM	0.2747**	0.2821**	0.2740**	0.2787**	0.2781**
	(0.0431)	(0.0462)	(0.0458)	(0.0460)	(0.0465)
RegARM	0.4526**	0.4302**	0.4140**	0.4044**	0.4062**
	(0.0653)	(0.0634)	(0.0625)	(0.0631)	(0.0634)
LTV1	0.0231**	0.0240**	0.0239**	0.0255**	0.0256**
	(0.0020)	(0.0020)	(0.0019)	(0.0015)	(0.0014)
PiggyBack	0.5375**	0.5424**	0.5469**	0.5389**	0.5379**
	(0.0376)	(0.0333)	(0.0312)	(0.0317)	(0.0313)
Interest	0.0724**	0.0682**	0.0659**	0.0704**	0.0701**
	(0.0084)	(0.0070)	(0.0076)	(0.0070)	(0.0070)
FICO	−0.8210**	−0.8078**	−0.8101**	−0.8059**	−0.8066**
	(0.0426)	(0.0426)	(0.0424)	(0.0380)	(0.0377)
FullDoc	−0.3477**	−0.3516**	−0.3474**	−0.3518**	−0.3522**
	(0.0346)	(0.0364)	(0.0365)	(0.0345)	(0.0345)
Investor	0.0777	0.0714	0.0716	0.0823	0.0828
	(0.0445)	(0.0452)	(0.0463)	(0.0440)	(0.0440)
Purchase	−0.0125	−0.0198	−0.0092	−0.0179	−0.0184
	(0.0150)	(0.0159)	(0.0144)	(0.0162)	(0.0161)
LoanAmount	0.0030	0.0045**	0.0046**	0.0030	0.0029
	(0.0026)	(0.0016)	(0.0015)	(0.0019)	(0.0019)
LoanAge	−0.5046**	−0.5411**	−0.5917**	−0.5659**	−0.5620**
	(0.0144)	(0.0203)	(0.0319)	(0.0276)	(0.0295)
PrepayPenalty	0.1124	0.1442	0.1466**	0.1852**	0.1843**
	(0.0620)	(0.0564)	(0.0569)	(0.0579)	(0.0579)
RateDiff	−0.3650**	−0.3120**	−0.2533**	−0.3502**	−0.3620**
	(0.0425)	(0.0392)	(0.0239)	(0.0376)	(0.0314)
PastAppr	−1.0549**	−1.3477**	−0.9493**	−1.5329**	−1.2967**
	(0.1647)	(0.1262)	(0.1475)	(0.1470)	(0.1414)
Lag Unemployment	−0.2018**	−0.2272**	−0.2463**	−0.2736**	−0.2702**

Continued on next page

	(1) No Delay	(2) With Delay	(3) Year	(4) Mean	(5) Smooth
	(0.0274)	(0.0300)	(0.0315)	(0.0483)	(0.0477)
Income	−0.0300	0.0396	0.0186	0.0408	0.0424
	(0.1725)	(0.1563)	(0.1494)	(0.1290)	(0.1301)
Rent	0.1055	0.0852	0.1026	−0.0481	−0.0456
	(0.2155)	(0.1511)	(0.1510)	(0.1409)	(0.1397)
Population	−0.0061	0.0401	0.0311	0.0368	0.0364
	(0.0461)	(0.0455)	(0.0454)	(0.0375)	(0.0373)
White	0.0288	0.0048	0.0094	−0.0469**	−0.0473**
	(0.0405)	(0.0350)	(0.0377)	(0.0175)	(0.0175)
Age65	0.0067	−0.0172	−0.0052	0.0264	0.0272
	(0.0267)	(0.0332)	(0.0313)	(0.0300)	(0.0298)
Education	−1.2855**	−1.2222**	−1.2992**	−1.2034**	−1.2043**
	(0.2802)	(0.3048)	(0.3091)	(0.2983)	(0.2991)
SchoolageChildren	0.4840	0.8627	0.8846	0.5197	0.5157
	(0.4255)	(0.5915)	(0.5479)	(0.4202)	(0.4175)
CommuteTime	0.3779	0.2437	0.2113	0.1260	0.1305
	(0.1672)	(0.1798)	(0.1762)	(0.0688)	(0.0709)
SameHouse	0.1434	−0.3609	−0.3252	−0.5641**	−0.5690**
	(0.3265)	(0.2235)	(0.2055)	(0.1715)	(0.1741)
Default(in%)			3.13		
Number of Obs			4118336		
LikelihoodRatio	127756	129484	116217	125904	125834
-2 lnL	2991728	2989999	2753202	2487099	2487170

** $p < 0.01$

Across various specifications, foreclosure delay consistently shows a statistically significant effect in increasing the borrower's propensity to default.[15] The results are consistent with the prediction of Ambrose et al. (1997) theoretical paper. The next important question is, whether the expected benefit from default has a material economic effect on default propensity? To make the economic significance of foreclosure delays clearer, Table 2.4 reports the marginal effects and equivalent changes associated with a given month increase in foreclosure delay corresponding to the two different measures of delay as in regression four and five. The marginal effects represent the percentage change in the hazard ratio associated with an increase of the delay. Since hazard ratio is not very intuitive,[16] a more intuitive way to gauge the economic importance of a variable is by comparing the marginal effects between variables in the same regression. That is by calculating the equivalent changes in other variables corresponding to the same marginal effects of the variable of interest. We pick updated LTV ratio and Fico score as the benchmark variables since those are important risk factors and are also continuous variables. Based on state mean foreclosure measures as in regression four, a three-month increase in foreclosure time increases the hazard of default by 32.58 percent ($\exp(0.094 \cdot 3) - 1 = 32.58\%$). In terms of equivalent changes, that matches the same marginal effect of increasing the LTV ratio by 11.06 percent ($\exp(0.0255 \cdot 11.06) - 1 = 32.58\%$), or a decrease in the Fico score by 34.99 points ($\exp(-0.8059 \cdot -34.99/100) - 1 = 32.58\%$). Note that these estimates are based on the overall sample including those borrowers with positive equity on their house.

[15] As a robustness check, the results are similar when using lagged state median foreclosure delays as the proxy for borrower expected delays.

[16] For example, for the Cox hazard model, the marginal effect tends to be larger for all variables for samples with lower default rates and be lower for samples with higher default rates.

For borrowers with negative equity, we expect that the economic impact would be even stronger.

TABLE 2.4. Marginal Effects of Foreclosure Delays and Equivalent Changes in Other Variables

	Increase in Foreclosure Delay (in month)			
Variable	1	2	3	6
Panel A		State Mean		
Marginal Effect (%)	9.86	20.68	32.58	75.77
LTV1 (%)	3.69	7.37	11.06	22.12
FICO	−10.94	−21.89	−32.83	−65.66
Panel B		Smooth		
Marginal Effect (%)	10.66	22.46	35.51	83.64
LTV1 (%)	3.96	7.91	11.87	23.74
FICO	−12.56	−25.12	−37.68	−75.35

Other explanatory variables have the expected signs. The results show that default reflects borrower expectations, incentives, and preferences. Specifically, borrowers with less equity as measured by a higher updated LTV ratio, second lien status, and thus with less equity, have a higher propensity to default. Borrowers that have selected more exotic and complicated loans have a higher propensity to default. Borrowers with a lower credit score and less documentation are more likely to default. Borrowers with a greater payment burden such as those with higher contract rates or higher borrowed amounts tend to have a higher chance of default. Borrower with a longer payment history are less likely to default. Areas with better educated population reduce the probability of default. Macroeconomic conditions also affect the performance of loans.

2.4.2 Robustness Checks

This section conducts robustness checks of the impact of foreclosure time on borrower's default behavior. Because regression four has the highest model fit as shown in Table 2.3, we pick regression four as our baseline regression. All following regressions in this section and next section include the same explanatory variables as the baseline regression, including the state fixed effect and using the lag year state mean foreclosure delay.

Our first concern is whether the effect is driven by a specific state. For example, California constitutes a substantial proportion of our sample. In order to check this, we take one state out of the sample at a time and run the regression using the mortgages from the rest of the states, Table 2.5 reports the results for the five largest states in our sample.[17] Panel A reports the estimate and model fit statistics and panel B reports the marginal effect and the equivalent changes corresponding to a three-month increase in delay. The results show that the impact of delay is not driven by a specific state. The marginal effect of a three-month increase in delay, is equivalent to an increase of LTV ratio by 10.14 percent to 18.20 percent or a 31.81 to 58.43 points decrease in Fico score. Interestingly, when California or Florida is taken out of the sample, the impact of delay is increased, although the increase might not necessarily be significant.

Our second concern is the accuracy of the data since mortgage data has many limitations. Typically, borrower characteristics are measured carefully only at origination. After origination, most servicers do not rescore the borrower's credit or reappraise the property value using either traditional appraisals or automated valuation models. In addition, most data files do not contain accurate amounts for junior liens after origination. Consequently, the most accurate data exists at origination. In order to control for the accuracy of data, we report the results by tracking the first one, two, three or four years of loan performances after loan origination. Table 2.6 reports the estimate and the comparative statics. The magnitude

[17]Other states have similar results. For simplicity, we included only the largest states results.

TABLE 2.5. Robustness Checks by Taking One State Out Each Time

Panel A	(1) CA	(2) NY	(3) IL	(4) FL	(5) NJ
ForeclosureDelay	0.1486**	0.1123**	0.0871**	0.1147**	0.0852**
	(0.0188)	(0.0284)	(0.0203)	(0.0266)	(0.0253)
Default(in%)	3.31	3.12	3.06	2.93	3.13
Number of Obs	2307318	3648457	3664935	3739133	3756776
LikelihoodRatio	68239	113873	115853	114492	116768
-2 lnL	1403227	2252045	2216541	2193598	2330156
Panel B	**Marginal Effects (3M) and Equivalent Changes**				
Marginal Effect (%)	56.17	40.06	29.86	41.07	29.12
LTV1 (%)	18.20	13.42	10.33	12.65	10.14
FICO	−58.43	−41.99	−32.08	−41.23	−31.81

** $p < 0.01$* $p < 0.05$

of statistical and economical significance is relatively stable across the different specifications.

Overall, after considering state specific effects, geography, different measurements of delay, and number of years that loan performances are tracked, the results show that the expected delays have a significant impact on the default behavior of borrowers.

2.4.3 LTV Ratio and Expected Delay

Ambrose et al. (1997) used numerical simulation to show that loans with higher initial LTV ratio are more sensitive to expected delay change. The magnitude of effect are larger for high LTV ratio loans. This section empirically investigates the sensitivity to the change in expected delay for different initial LTV ratio loans.

Rational borrowers will not choose to default whenever they have positive equity in the house since they could sell the house in the market and make a higher profit relative to defaulting and giving the house back to the lender. Negative equity is a necessary but not sufficient condition for default because of the value of waiting to

TABLE 2.6. Robustness Checks by Number of Years of Loan Performance Tracked

Panel A	(1) One Year	(2) Two Years	(3) Three Years	(4) Four Years
ForeclosureDelay	0.1094*	0.1354**	0.1011**	0.0949**
	(0.0542)	(0.0469)	(0.0195)	(0.0218)
Default(in%)	0.94	1.92	2.72	3.09
Number of Obs	666546	2197112	3279224	3865093
LikelihoodRatio	7394	47284	93570	118313
-2 lnL	108637	820970	1745491	2343463

Panel B	Marginal Effects (3M) and Equivalent Changes			
Marginal Effect (%)	38.85	50.11	35.43	32.94
LTV1 (%)	10.55	13.91	11.11	10.99
FICO	−55.21	−51.37	−37.30	−35.27

** $p < 0.01$* $p < 0.05$

default, transaction costs, and reputation costs (Kau and Kim, 1994; Kau et al., 1994; Foote et al., 2008). Higher initial combined LTV ratio loans are less resistant to house price depreciation and more likely to have an "in the money" default option. When the default option is "in the money," foreclosure delay tends to have a material effect on changing the borrower's propensity to default.

Table 2.7 reports the results by different initial combined LTV ratio subsamples. For loans with combined LTV ratio greater than 80 percent, the borrower's default decision is statistically very sensitive to expected delay. As the combined LTV ratio decreases, to below 80 percent, the statistical significance declines, and the effect disappears when combined LTV ratio is less than 70 percent. As for economic significance, the magnitudes of effect are much higher for loans with combined LTV ratio greater than 95 percent than loans with combined LTV less than 80 percent. Our empirical findings are very consistent with the theoretical prediction. The results indicate that in a deteriorated housing market, when borrowers are likely to have negative equity, the increase in expected delay tends to have a larger and more significant impact in increasing default.

TABLE 2.7. Subsamples by Initial CLTV Ratios

Panel A	(1) CLTV<70	(2) 70-80	(3) 80-90	(4) 90-95	(5) 95-100	(6) 100<CLTV
ForeclosureDelay	0.0360	0.0649*	0.0627**	0.0483**	0.1235**	0.1491**
	(0.0327)	(0.0305)	(0.0235)	(0.0180)	(0.0271)	(0.0268)
Default(in%)	1.18	2.34	3.51	4.48	4.65	6.16
Number of Obs	1136076	798112	626715	441045	192625	514574
LikelihoodRatio	18216	16958	28347	12579	5391	12936
-2 lnL	218957	302258	610022	304996	120200	501589

Panel B	Marginal Effects (3M) and Equivalent Changes					
Marginal Effect (%)		21.49	20.70	15.59	44.85	56.41
FICO		−19.42	−23.16	−19.50	−51.32	−73.39

** $p < 0.01$ * $p < 0.05$

Next we investigate if the effect of expected delay is sensitive to different loan types or borrower's credit score. We focus on loans with initial combined LTV greater than 95 percent. Table 2.8 report the results of subsamples of different loan types. Table 2.9 reports the results of the subsamples according to different borrower's credit score. Across different types of loans and different borrower's credit scores, expected delays consistently increase the default propensity. For very high credit score borrowers, the effect is only significant at the 5 percent level. This may due to the cost of damaging credit score and reputation cost, which may offset the benefits from "free rent."

In conclusion, the effect of foreclosure delay is stronger when borrowers are likely to have negative equity such as in the current housing market. The increase in foreclosure time might change borrower's expected benefit from default, and thus at the margin make default the optimal decision.

TABLE 2.8. Subsamples by Loan Types for Initial CLTV>95% Loans

Panel A	(1) ExoticARM	(2) HybridARM	(3) ExoticFRM	(4) FRM
ForeclosureDelay	0.1598**	0.1311**	0.2023**	0.1469**
	(0.0271)	(0.0503)	(0.0222)	(0.0534)
Default(in%)	6.70	7.05	4.68	2.79
Number of Obs	315420	84495	69179	66265
LikelihoodRatio	7257	2045	1549	1362
-2 lnL	329078	74655	39314	20763

** $p < 0.01$* $p < 0.05$

TABLE 2.9. Subsamples by Fico Scores For Initial CLTV>95% Loans

Panel A	(1) Fico≤620	(2) 620-660	(3) 660-700	(4) 700-740	(5) 740-780	(6) 780<Fico
ForeclosureDelay	0.1200**	0.1818**	0.2174**	0.2278**	0.1945**	0.1553*
	(0.0336)	(0.0355)	(0.0453)	(0.0356)	(0.0476)	(0.0791)
Default(in%)	9.61	7.84	6.27	5.01	3.80	3.01
Number of Obs	54715	91792	143469	138947	82736	25646
LikelihoodRatio	61165	90914	124120	96862	40845	18327
-2lnL	966	1539	2361	2543	1517	343

** $p < 0.01$* $p < 0.05$

2.5 Conclusion

The benefit of default rises with the length of the interval between the first missing payment and the date of foreclosure sale. Therefore, the higher option value associated with the expected longer foreclosure periods increase the incentive to default.

This paper empirically investigates the influence of expected foreclosure delays on borrower's default propensities. The paper uses the *actual* time-varying state-level foreclosure times as proxies for the borrowers' expected benefit from default in the form of "free rent." While existing literature includes a single-year state non-contested foreclosure times as proxies for lengthiness of the foreclosure process, our measure includes the *actual* delay and captures the variation in foreclosure delays over time. We document the increase of delay in recent years and find a statistically and economically significant impact of expected delay on borrower default behavior. The results are robust to various specifications including state fixed effects, different measures for delays, and temporal fixed effects. The results are not driven by major states in the sample nor by the number of years of tracked loan performances. For high initial combined LTV ratio mortgages, the delay has stronger impact on default and the effect is consistent across various loan types and borrowers with different credit scores. Our empirical findings are consistent with the predictions of Ambrose et al. (1997) theoretical paper.

From the viewpoints of elected leaders in state and local government, not much good comes from foreclosures. Mortgage borrowers are potential voters and survival bias ensures that elected leaders pay attention to such groups. Therefore, it is tempting for officials such as elected judges, sheriffs, and legislators to delay the foreclosure process through slow performance or through more explicit tactics such as a moratorium.

However, this research offers evidence of the potential negative effects arising from longer foreclosure periods. Longer periods of *de facto* or *de jure* forbearance increase borrowers' incentives to default which may result in more borrowers entering into default. In the current market condition with many borrowers having negative equity, the longer delay tends to have a larger magnitude of impact on default, which may make default an optimal decision for more borrowers. The negative effects of longer foreclosure delay might need to be taken into consideration whenever taking action trying to mitigate the foreclosure crisis.

Chapter 3

Using Housing Futures in Mortgage Research

3.1 Introduction

Economic decisions often rely on expectations of variables in the future. This presents a difficulty when working with empirical data since most variables represent the outcomes of past decisions and therefore may imperfectly capture such expectations.

For example, the expected house price plays a role in individual default decision since this affects both the benefit and the cost of making mortgage payments through the perceived value of the property and the option to default in the future (Kau and Kim, 1994; Ambrose et al., 1997; Foote et al., 2008). While many researchers (e.g., Shiller, 2007) pay attention to the role of housing expectations in the current mortgage crisis, obtaining a reasonable proxy for expected housing appreciation is a challenge. The fundamental difficulty is that market expectations are typically not directly observable. Because of this difficulty, current empirical mortgage research either (1) does not include housing expectation proxies in empirical models (e.g., Demyanyk and Van Hemert, 2009), (2) uses past housing appreciation (e.g., Bajari et al., 2008), or (3) uses a time series forecast (e.g., Goetzmann et al., 2009) as the proxy.

This paper proposes a new proxy of housing expectations in mortgage models by using the information from the transaction prices of Case-Shiller housing futures. Since the contract prices of futures are based on market participants' beliefs concerning future housing prices, the transaction prices incorporate the market expectation of housing prices.[1]

This paper compares the performances of four different housing expectation proxies in explaining default behavior. The four proxies are futures, past year appreciation from the Case-Shiller house price index (CSI), past year appreciation from the Federal Housing Finance Agency house price index (FHFA), and time series forecasts. In addition, we investigate the additional information content of futures that is not contained in the past price based measures.

The results show that futures are a promising proxy for housing expectations. First, futures have the highest regression model fit among all four measures. This indicates that futures might explain default behavior better than other measures. Second, only futures consistently show that higher housing expectations lower the default propensity, as theory suggests. Other measures either exhibit mixed signs or are statistically insignificant. Third, even after combining other proxies in the same regression, the coefficient estimates and standard errors of futures remain about the same as with only futures in the regressions. This reveals that futures contain information not captured by historical prices.

The rest of the paper proceeds as follows: Section 3.2 introduces the data and variables, Section 3.3 presents the empirical results, and Section 3.4 concludes.

3.2 Data, Variables and Summary Statistics

This section first describes data sources and sample selection in Section 3.2.1, then introduces variables and specifications in Section 3.2.2, and the summary statistics in Section 3.2.3.

[1]Financial futures are viewed as the market expectation of underlying product price movements in financial derivative literature. For example, the Federal funds futures are widely used as the market expectations of future monetary policies (e.g., Krueger and Kuttner, 1996; Grkaynak et al., 2007).

3.2.1 Data

The S&P/Case-Shiller home price indices (CSI) and the contract prices of housing futures with CSI as the underlying asset are from Bloomberg at the metropolitan (MSA) level. Housing futures are traded on the Chicago Mercantile Exchange (CME). House price indices from the Federal Housing Finance Agency (FHFA) are downloaded from their website at the MSA level.[2] The loan-level data comes from Blackbox Logic's BBx.[3] BBx covers over 90 percent of US non-agency residential securitized deals.[4] BBx has detailed mortgage origination information and monthly updates of mortgage payment information. Unemployment data is from the Bureau of Labor Statistics at the MSAs level. National average 30 year fixed rate mortgage (FRM) interest rates are from Freddie Mac's national mortgage survey. The zip code level household median incomes are from the 2000 Census.

Our sample includes single family, first lien loans with a 30 year contract term in the ten MSAs with housing futures transactions. We include mortgages originated between May 2006, when housing futures started trading on CME,[5] to December 2007 and track the loan performances quarterly through December 2009.[6] Mortgages are limited to those entering the dataset within three months of origination to control for survival bias. The number of loan-quarter observations is 1.7M, with default rate equal to 4.12%.

3.2.2 Variables

The event of interest is default, which is defined as the first 90 days delinquency. At each time period, the status of the loan could be in default, prepaid in full, or

[2] FHFA website: www.fhfa.gov

[3] BBx data is similar to Loan Performance data. BBx data information is available at www.bbxlogic.com/data.htm.

[4] Since our data is from privately securitized loans, the results may apply only to this set of mortgages.

[5] Although Case et al. (1993) have long been advocating a derivative market for housing in US, it was not until May 2006 that such a market was established.

[6] After 2007, because of the mortgage crisis, very few newly originated loans were added into the dataset.

censored.[7] If the loan is either in default or prepaid, all subsequent observations are dropped out of the sample. Explanatory variables include housing expectations, loan/borrower characteristics, lagged unemployment rates, neighborhood median income and controls for prepayment risk. The variable definitions appear in Table 3.1.

This study examines four measures of housing expectations. The futures proxies are inferred from the transaction prices of housing futures. The CME issues futures contracts each quarter in February, May, August, and November. Market participants include builders and developers, lenders, mortgage portfolio managers, mutual funds, other financial institutions, and individual investors. We first calculate the average transaction prices of futures in the trading month one year before the maturity date, then divide the number by lagged two months CSI, and minus one to get the quarterly expectations.[8] Next we linearly interpolate the quarterly data to get the monthly expectations. The second measure is the previous one year appreciation from CSI. The third measure is the previous one year appreciation from the FHFA index.

The fourth measure is the one year forecasts from time series model based on CSI. We decide to use the autoregressive integrated moving average (ARIMA) model since this is the most commonly used time series model. Seasonal factors are included in the model to account for the seasonal pattern of housing prices. We first select the lags of the model, then use a 20 year rolling time window to fit the data each month for each MSA area, then forecast. This approach is more dynamic and allows the model to incorporate the new information for each time period. The

[7] Loan status other than default or prepaid is considered censored which includes uninformative censoring and current status.

[8] Lagged two months HPI is used since the release of CSI is lagged by two months and that represents the information available at the transaction time.

TABLE 3.1. Variable Definitions

Variable	Definition
Default	First 90 days delinquency.
Expectation	Proxies for housing appreciation expectation.
Futures	Housing expectation derived from housing futures.
Past CSI	Past year appreciation from CSI.
Past FHHA	Past year appreciation from FHFA housing index.
Time Series	Time series forecast of next year housing appreciation.
CLTV	HPI updated current loan-to-value ratio.
Piggyback	Dummy variable, =1 if the property has junior liens at origination, =0 otherwise.
Interest	Initial contract rate of the mortgage.
FICO	Fair, Isaac and Company credit score of the borrower at origination, scaled by 100.
FullDoc	Dummy variable, =1 if borrower offers full documentation for loan application, =0 otherwise.
ExoticARM	Dummy variable, =1 if adjustable rate mortgage with deferred amortization provisions including interest only, negative amortization and/or balloon payment, =0 otherwise.
HybridARM	Dummy variable, =1 if adjustable rate mortgage with fixed initial interest rate, no deferred amortization provisions, =0 otherwise.
RegARM	Dummy variable, =1 if adjustable rate mortgage with no fixed initial interest rate, no deferred amortization provisions, =0 otherwise.
ExoticFRM	Dummy variable, =1 if fixed rate mortgage with deferred amortization provisions including interest only and/or balloon payment, =0 otherwise.
FRM	Dummy variable, =1 if fully amortized fixed rate mortgage, =0 otherwise.
Investor	Dummy variable, =1 if the purpose of the use of the house as an investment, =0 otherwise.
Purchase	Dummy variable, =1 if new purchase, =0 otherwise.
LoanAmount	The original loan amount, scaled by 10000.
LoanAge	Loan age in year.
PrepayPenalty	Dummy variable, =1 if the loan has prepayment penalty, =0 otherwise.
RateDiff	Difference of 30 year national average FRM rate between current period and at loan origination.
Lag Unemployment	Lagged unemployment rate at MSA level.
Income	Log median household income at zip code level.

selection criteria for the lags is to make all 44 (from May 2006 to December 2009) rolling window regressions converge for each MSA. Due to the unusual housing price movements in our sample time period, the time series regressions do not converge in many cases when using longer lags. Therefore, we use relatively short time period lags in our model. Eight MSAs use ARIMA(12, 1, 0) and two MSAs use ARIMA(6, 1, 0). We use a simple time series model since simple models often perform better in forecasting competitions (Makridakis et al., 1983).

3.2.3 Summary Statistics

Table 3.2 reports the summary statistics of the different proxies for housing expectations for the ten MSA areas. Several patterns appear. First, at the average level, different proxies yield quite different means and distributions. For example, in Las Vegas, futures point to a less than four percent depreciation and other measures forecast more than ten percent depreciation. However in Denver, expectations from housing futures have the largest predicted depreciation. In general, housing futures have smaller dispersion than other measures. Second, previous year appreciations from CSI and FHFA also show differences. In nine out of ten MSAs, the past CSI displays greater volatility of housing appreciation over time. Past CSI also points to more pessimistic expectations than the past FHFA indices in all ten MSA areas. The main reason for the difference of the two indices lies in the different composition of the underlying assets. FHFA includes only mortgages purchased by Fannie Mae or Freddie Mac, while CSI has a broader coverage of underlying properties. Other reasons are that FHFA uses both transaction and appraisal values while CSI uses only transaction prices, and the weight given to properties with longer intervals between transactions are also different (Leventis, 2008). Third, time series forecasts show the largest dispersion in both the standard deviation and the range of estimates in all MSAs. Time series forecasts sometimes vary greatly. For example, in San Francisco area, the most optimistic housing expectation is a 30 percent appreciation while the most pessimistic estimate is a 66 percent depreciation.

Table 3.3 reports the Pearson correlation coefficients between futures and other housing expectation proxies. The number in the parenthesis under the correlation coefficients is the p-value for the null hypothesis that the correlation coefficient is not different from zero. First, note that the correlation coefficients are relatively low with the highest number being slightly higher than 0.7. Using a one percent significance level, past year appreciations from CSI and FHFA each have three areas that are significantly positively correlated with housing futures expectations. Time series forecasts have five MSAs that show significant correlations (although in the Boston area, the correlation is negative). The results show that futures are not highly correlated with other proxies. Both Table 3.2 and 3.3 indicate that futures seem to be a quite different proxy from those measures that are extrapolated from past housing prices.

3.3 Empirical Results

This section first introduces the estimation model in Section 3.3.1, then investigates the performances of various proxies for housing expectations in explaining default in Section 3.3.2, checks for robustness in Section 3.3.3, and studies the additional information content of futures in Section 3.3.4.

3.3.1 Cox Proportional Hazard Model

The empirical analysis is conducted in the Cox proportional hazard model setting (Cox, 1972) to investigate the factors that may affect the probability of default. The advantages of the Cox model include that it can handle right censoring and take time from origination to default into consideration. Also the Cox model is

TABLE 3.2. Summary Statistics for Housing Expectation Proxies (in %)

Variable	Mean	Std Dev	Min	Max
CBSA=14460		Boston		
Futures	−4.6808	2.4590	−8.2995	0.8356
Past CSI	−4.5346	1.9237	−8.0053	0.4770
Past FHFA	−3.3554	1.2550	−4.6500	0.4500
Time Series	−4.7547	3.5673	−13.5731	0.3566
CBSA=16980		Chicago		
Futures	−3.8792	3.2886	−11.7906	5.0852
Past CSI	−5.8422	7.8466	−18.6532	7.6849
Past FHFA	−1.7398	5.3723	−8.9900	7.8100
Time Series	−6.4855	12.4193	−43.6911	7.2820
CBSA=19740		Denver		
Futures	−4.5125	2.6685	−9.3917	2.3516
Past CSI	−2.2830	2.6382	−5.6881	2.7772
Past FHFA	−0.3121	0.7899	−1.8033	1.7400
Time Series	−1.5451	3.6862	−9.6517	4.6329
CBSA=29820		Las Vegas		
Futures	−3.2647	9.3398	−15.7927	20.2125
Past CSI	−16.7394	14.4210	−32.9763	7.8746
Past FHFA	−12.7186	14.2806	−33.7300	11.1800
Time Series	−17.9104	19.2441	−57.2766	8.0753
CBSA=31100		Los Angeles		
Futures	−6.7893	4.9870	−22.0934	6.4944
Past CSI	−10.5712	12.7485	−27.9279	14.9738
Past FHFA	−5.6660	11.4961	−20.7400	18.9000
Time Series	−12.1778	19.2989	−52.6732	21.3298
CBSA=33100		Miami		
Futures	−4.8379	6.3580	−17.6105	7.7476
Past CSI	−12.3374	15.6310	−29.4916	22.7125
Past FHFA	−5.6470	16.5448	−26.8300	24.4500
Time Series	−13.8387	20.4941	−64.5320	26.1679
CBSA=35620		New York		
Futures	−6.7376	3.6110	−13.5945	5.8181
Past CSI	−4.4843	5.7370	−12.3408	10.0071
Past FHFA	−1.0267	4.9428	−6.1100	10.4800
Time Series	−5.3705	6.5273	−22.1037	7.2710
CBSA=41740		San Diego		
Futures	−6.1728	3.5785	−16.6525	−0.2580
Past CSI	−12.2356	9.6607	−26.6796	2.9504
Past FHFA	−8.3371	6.4701	−18.3300	4.5400
Time Series	−13.0589	16.8154	−42.7009	19.9926
CBSA=41860		San Francisco		
Futures	−4.6960	5.0612	−17.3298	12.8699
Past CSI	−12.2505	12.5798	−32.3214	6.2524
Past FHFA	−3.7273	5.3107	−9.9900	8.1000
Time Series	−9.6472	23.1448	−66.1301	30.5781
CBSA=47900		Washington		
Futures	−3.3486	3.6889	−10.6316	6.7367
Past CSI	−8.4485	7.6645	−19.5970	9.2226
Past FHFA	−3.8395	7.5117	−13.7100	13.9700
Time Series	−6.9899	14.0464	−28.1107	29.8525

TABLE 3.3. Pearson Correlation Coeffients between Housing Expectations from Futures and other Proxies

CBSA	Past CSI	Past FHFA	Time Series
14460	−0.2946	0.0568	−0.3945
	(0.0522)	(0.7144)	(0.0081)
16980	0.3189	0.2267	0.3061
	(0.0348)	(0.1389)	(0.0433)
19740	0.2142	0.2909	−0.0256
	(0.1626)	(0.0554)	(0.8692)
29820	−0.2170	−0.1431	−0.1058
	(0.1571)	(0.3541)	(0.4942)
31100	0.6279	0.5664	0.6907
	(0.0000)	(0.0001)	(0.0000)
33100	0.1331	−0.1433	0.5612
	(0.3892)	(0.3535)	(0.0001)
35620	0.7036	0.6560	0.7080
	(0.0000)	(0.0000)	(0.0000)
41740	0.5169	0.4820	0.7094
	(0.0003)	(0.0009)	(0.0000)
41860	−0.0323	0.0935	0.0203
	(0.8352)	(0.5459)	(0.8958)
47900	0.0599	−0.0459	−0.0234
	(0.6994)	(0.7673)	(0.8800)

a semi-parametric technique that does not require choosing a specific probability distribution of the survival time, and is considered a more robust approach.

The model specification is as in (3.1), where $h(t)$ is the hazard function of default and $\lambda_0(t)$ is called the baseline hazard function. The explanatory variables in X include both static variables which are obtained at origination and time-varying variables which are updated quarterly. The event of interest is default, with prepayment as the competing risk.

$$h(t, X) = \lambda_0(t) \exp(X\beta) \tag{3.1}$$

3.3.2 Housing Expectations and Default

In making the decision to default, borrowers weigh the benefit of keeping the house versus the cost of making the mortgage payments. Expected house prices play a central role in the valuation process. On the one side, the value of house to the borrower includes the expected future house price. On the other side, as Kau and Kim (1994) and Kau et al. (1994) noted, the cost of the mortgage payments to the borrower needs to take into consideration the value of the future default option. This future default option value is affected by the expected future house price. Foote et al. (2008) used a two time period model to illustrate that higher expectations of future house prices reduce the incentive to default even in face of current negative equity since borrowers are in hope of market recovery in the future, which may bring them to positive equity.

Despite of the importance of housing expectations, the existing proxies are mainly model based and backward-looking in nature. In a normal housing market when housing prices are relatively predictable, these measures might work well. However, in the recent housing market, those model based measures performed poorly in forecasting housing price movements (Goetzmann et al., 2009). Also, since model based measures rely solely on past price information, the same variable such as past year appreciation may represent both the past market condition and expectation, which makes it difficult to disentangle the two effects.

We first compare the regression results with different proxies of housing expectations. Table 3.4 reports the coefficient estimates, with the state clustered standard error in the parenthesis. The first regression has expectations inferred from transaction prices of futures. The second uses the past year appreciation of CSI. The third one uses the past year appreciation from FHFA and the last one uses the one-year time series forecasts of housing appreciation from the ARIMA models.

The results show that futures behave differently from other proxies. First, from the model fit perspective, futures yield the highest model fit as measured by -2ln L among four different proxies. This indicates that futures might capture the true expectations better than other proxies. Second, coefficients of futures and time series have negative signs which suggest that higher housing expectations lower the probability of default, while both measures of past appreciation have positive signs. Futures also have the largest magnitude estimates. Third, as for statistical significance, only futures are significant at the one percent significance level. In sum, futures are the only measure that shows that higher housing expectations significantly reduce the default propensity as predicted by theory. The overall results suggest that different proxies could lead to quite different inferences concerning the role of housing expectations. Although inaccurate proxies may indicate that housing expectations do not play an important role in default decisions, futures seem to conform more closely to our prior beliefs.

From futures estimation as in Table 3.4, a one percent increase in housing expectation decreases the hazard of default by 1.32 percent $(\exp(-0.0133 \cdot 1) - 1 =$

TABLE 3.4. Different Proxies for Housing Expectations

	Futures	Past CSI	Past FHFA	Time Series
Expectation	-0.0133^{**}	0.0020	0.0076	-0.0018
	(0.0040)	(0.0037)	(0.0036)	(0.0012)
CLTV	0.0229^{**}	0.0228^{**}	0.0238^{**}	0.0218^{**}
	(0.0018)	(0.0020)	(0.0015)	(0.0022)
PiggyBack	0.5780^{**}	0.5771^{**}	0.5759^{**}	0.5778^{**}
	(0.0380)	(0.0393)	(0.0387)	(0.0398)
Interest	0.0749^{**}	0.0744^{**}	0.0737^{**}	0.0753^{**}
	(0.0079)	(0.0075)	(0.0073)	(0.0080)
FICO	-0.7787^{**}	-0.7741^{**}	-0.7742^{**}	-0.7765^{**}
	(0.0406)	(0.0421)	(0.0426)	(0.0428)
FullDoc	-0.3856^{**}	-0.3926^{**}	-0.3976^{**}	-0.3865^{**}
	(0.0466)	(0.0505)	(0.0481)	(0.0475)
ExoticARM	0.5439^{**}	0.5464^{**}	0.5372^{**}	0.5499^{**}
	(0.0418)	(0.0453)	(0.0462)	(0.0432)
HybridARM	0.5855^{**}	0.5803^{**}	0.5680^{**}	0.5876^{**}
	(0.0238)	(0.0265)	(0.0263)	(0.0237)
ExoticFRM	0.2199^{**}	0.2231^{**}	0.2200^{**}	0.2248^{**}
	(0.0490)	(0.0495)	(0.0500)	(0.0486)
RegARM	0.3725^{**}	0.3635^{**}	0.3563^{**}	0.3717^{**}
	(0.0652)	(0.0627)	(0.0668)	(0.0643)
Investor	0.0851	0.0778	0.0818	0.0741
	(0.0470)	(0.0495)	(0.0492)	(0.0480)
Purchase	-0.0066	-0.0054	-0.0114	0.0009
	(0.0189)	(0.0184)	(0.0151)	(0.0204)
LoanAmount	0.0004	0.0024	0.0023	0.0020
	(0.0056)	(0.0030)	(0.0031)	(0.0038)
LoanAge	-0.4098^{**}	-0.4272^{**}	-0.4354^{**}	-0.4339^{**}
	(0.0246)	(0.0208)	(0.0202)	(0.0190)
PrepayPenalty	0.0215	0.0370	0.0454	0.0270
	(0.0491)	(0.0455)	(0.0434)	(0.0500)
RateDiff	-0.1784^{**}	-0.1799^{**}	-0.1594^{**}	-0.1891^{**}
	(0.0589)	(0.0552)	(0.0588)	(0.0544)
Lag Unemployment	-0.1809^{**}	-0.1817^{**}	-0.1777^{**}	-0.1803^{**}
	(0.0349)	(0.0385)	(0.0381)	(0.0392)
Income	-0.3858^{**}	-0.4094^{**}	-0.4186^{**}	-0.4032^{**}
	(0.0651)	(0.0676)	(0.0689)	(0.0664)
-2lnL	1623539	1623892	1623747	1623826

** $p < 0.01$

-1.32%). An expected one percent decrease in housing expectation increases the hazard of default by 1.34 percent ($\exp(-0.0133 \cdot -1) - 1 = 1.34\%$). Given the pessimistic outlook of housing market, this indicates that the current large number of defaults might be partly due to strategic default which is caused by not only negative equity but also the low expectation of future housing prices.

Other variables have the expected signs. Higher current loan-to-value ratio, having a second lien, and a higher interest rate lead to higher propensity to default. Higher Fico scores and full documentation decrease the propensity to default. Various exotic loans increase the propensity to default relative to the fully amortized fixed rate mortgages. Seasoned loans have a lower probability of default. Macroeconomic conditions such as the lagged unemployment also affect the loan performances. Neighborhoods with higher incomes have lower default rates.

3.3.3 Robustness Checks

Next we conduct various robustness checks by including year and/or state dummies to capture temporal and/or state fixed effects. Other variables and model specifications are the same as in Table 3.4. Table 3.5 reports the regression results. For simplicity, we only report the estimates of housing expectations. Panel A regressions include only annual dichotomous variables. Panel B regressions include only the state dichotomous variables and Panel C regressions include both state and year dichotomous variables. Across different specifications, futures consistently have a better model fit and the coefficients are significant and negative. Past CSI and past FHFA have mixed signs and remain insignificant. When year dummies are included, time series forecasts become significantly negative, but turn insignificant as state dummies are added in the regression.

TABLE 3.5. Robustness Checks

	Futures	Past CSI	Past FHFA	Time Series
Panel A	Year Dummies Included			
Expectation	-0.0195^{**}	-0.0013	0.0049	-0.0039^{**}
	(0.0050)	(0.0051)	(0.0052)	(0.0014)
-2lnL	1622616	1623286	1623216	1623076
Panel B	State Dummies Included			
Expectation	-0.0072^{**}	-0.0058	-0.0035	-0.0020
	(0.0028)	(0.0036)	(0.0057)	(0.0015)
-2lnL	1621696	1621756	1621759	1621731
Panel C	Year and State Dummies Included			
Expectation	-0.0121^{**}	-0.0095	-0.0129	-0.0030
	(0.0045)	(0.0067)	(0.0111)	(0.0014)
-2lnL	1619962	1620111	1619982	1620095

** $p < 0.01$

3.3.4 Information Content in Futures

In this section, we investigate the information content of futures. In Table 3.6, except for expectations variables, we use the same model specifications as the regressions in Table 3.4. For the expectations variables, each regression includes futures and some other proxies to study whether futures contain additional information besides the past housing appreciations. The results show that both coefficients and standard error estimates of futures are very consistent and stable across various specifications. The coefficients are negative and significant even after controlling for various combinations of past price information. This indicates that futures contain information that are not reflected in the past housing prices, which is not surprising since individuals use all the available information to form their expectations, not just past prices.

TABLE 3.6. Combination of Forecasts in Regression

	1	2	3	4	5	6	7
Futures	-0.0148^{**}	-0.0145^{**}	-0.0132^{**}	-0.0141^{**}	-0.0130^{**}	-0.0130^{**}	-0.0130^{**}
	(0.0041)	(0.0038)	(0.0045)	(0.0034)	(0.0046)	(0.0040)	(0.0041)
Past CSI	0.0049			-0.0025	0.0099		0.0018
	(0.0029)			(0.0063)	(0.0077)		(0.0116)
Past FHFA		0.0092^{**}		0.0111		0.0106	0.0096
		(0.0036)		(0.0066)		(0.0049)	(0.0070)
Time Series			-0.0001		-0.0032	-0.0017	-0.0021
			(0.0015)		(0.0034)	(0.0017)	(0.0036)
-2lnL	1623479	1623360	1623539	1623352	1623415	1623330	1623328

** $p < 0.01$

3.4 Conclusion

Housing price expectations play a role in borrower mortgage default decisions. However, because of the difficulty of obtaining a good proxy, prior mortgage research either does not include the housing expectations in the empirical work or uses a past price based approach.

This paper proposes to use information of housing futures contracts as an alternative proxy since the transaction prices incorporate expectations for future house prices. As an example, we compare the performances of four different proxies for expectations in explaining borrower mortgage default behavior. The results show that the futures based proxy outperforms other measures by having the highest regression model fit as well as being the only measure that shows a significant effect in the correct direction on mortgage default behavior. The results also show that futures contain additional information that is not contained in the past housing prices.

Since housing expectations may affect various real estate issues such as mortgage credit supply, housing demand and housing supply, the use of futures may help these other research areas.

References

Ambrose, B. W., R. J. Buttimer Jr., and C. A. Capone (1997). Pricing mortgage default and foreclosure delay. *Journal of Money, Credit and Banking 29*(3), 314–325.

Amidu, A., B. T. Aluko and J. A. Hansz (2008). “Client Feedback Pressure and the Role of Estate Surveyors and Valuers,” *Journal of Property Research*, 25, 89-106.

Bajari, P., C. S. Chu, and M. Park (2008). An empirical model of subprime mortgage default from 2000 to 2007. NBER working paper series.

Berkowitz, J. and R. Hynes (1999). Bankruptcy exemptions and the market for mortgage loans. *The Journal of Law and Economics 42*(2), 809–830.

Case, K. E., R. J. Shiller, and A. N. Weiss (1993). Index-based futures and options markets in real estate. *Journal of Portfolio Management 19*(2), 83–92.

Chinloy, P., M. Cho and F. I. Megbolugbe (1997). “Appraisals, Transaction Incentives, and Smoothing,” *Journal of Real Estate Finance and Economics* 14, 89-111.

Cox, D. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society. Series B (34)*, 187–220.

Demyanyk, Y. and O. Van Hemert (2009). Understanding the subprime mortgage crisis. *Review of Financial Studies*. forthcoming.

Diaz, J. and J. A. Hansz (2001). “The Use of Reference Points in Valuation Judgment,” *Journal of Property Research* 18, 141-148.

Dotzour, G. M. (1988). “The Impact of Professional Designation on Appraisal Variation in Corporate Relocation Appraisals,” *The Appraisal Journal* 56, 522-530.

Foote, C. L., K. Gerardi, and P. S. Willen (2008). Negative equity and foreclosure: Theory and evidence. *Journal of Urban Economics 64*(2), 234–245.

Freddie Mac (2009). “Home Valuation Code of Conduct,” March 31st.

Ghent, A. C. and M. Kudlyak (2010). Recourse and residential mortgage default: Theory and evidence from U.S. states. Working paper.

Goetzmann, W. N., L. Peng, and J. Yen (2009). The subprime crisis and house price appreciation. Working paper, available at: http://ssrn.com/paper=1340577.

Graff, A. R. and S. M. Young (1999). “Magnitude of Random Appraisal Error in Commercial Real Estate Valuation,” *Journal of Real Estate Research* 17, 33-54.

Grkaynak, R. S., B. P. Sack, and E. T. Swanson (2007). Market-based measures of monetary policy expectations. *Journal of Business and Economic Statistics 25*(2), 201–212.

Housing and Urban Development (2009). "Hud Secretary Donovan Announces Expanded Eligibility For Making Home Affordable Refinancing," *HUD News Release*, July 1st.

Kau, J. B., D. C. Keenan, and T. Kim (1994). Default probabilities for mortgages. *Journal of Urban Economics 35*(3), 278–296.

Kau, J. B., D. C. Keenan, and K. Taewon (1993). Transaction costs, suboptimal termination and default probabilities. *Journal of the American Real Estate and Urban Economics Association 21*(3), 247–263.

Kau, J. B. and T. Kim (1994). Waiting to default: The value of delay. *Journal of the American Real Estate and Urban Economics Association 22*(3), 539–551.

Krueger, J. T. and K. N. Kuttner (1996). The fed funds futures rate as a predictor of federal reserve policy. *Journal of Futures Markets 16*(8), 865–879.

Lam, N., R. K. Pace, R. Campanella, J. P. LeSage, and H. Arenas (2009). "Business Return in New Orleans: Decision Making Amid Post-Katrina Uncertainty," *PLoS ONE*, August.

LeSage, J. P. and R. K. Pace (2009). *Introduction to Spatial Econometrics*, Boca Raton: CRC Press/Taylor & Francis.

Leventis, A. (2008). Real estate futures prices as predictors of price trends. FHFA working paper.

Levitin, A. (2009). "Resolving the Foreclosure Crisis: Modification of Mortgages in Bankruptcy," *Wisconsin Law Review*, forthcoming.

LeSage, J. P. and R. K. Pace (2009). *Introduction to Spatial Econometrics.* Boca Raton: CRC Press/Taylor & Francis.

Levitin, A. J. (2010). Problems in mortgage servicing from modification to foreclosure: Hearing before the commettee on banking, housing, and urban affairs, 111th cong. Nov. 16, available at: http://scholarship.law.georgetown.edu/cong/112.

Lin, E. Y. and M. J. White (2001). Bankruptcy and the market for mortgage and home improvement loans. *Journal of Urban Economics 50*(1), 138–162.

Makridakis, S., S. Wheelwright, and V. McGee (1983). *Forecasting: methods and applications*. John Wiley, New York.

Pence, K. M. (2006). Foreclosing on opportunity: State laws and mortgage credit. *Review of Economics and Statistics 88*(1), 177–182.

Pennington-Cross, A. (2006). "The value of foreclosed property," *Journal of Real Estate Research* 28(2), 193-214.

U.S. Department of the Treasury (2009). "Home Affordable Modification Program Guidelines," March 4th.

Pennington-Cross, A. (2010). The duration of foreclosures in the subprime mortgage market: A competing risks model with mixing. *Journal of Real Estate Finance and Economics 40*, 109–129.

Shiller, R. J. (2007). Understanding recent trends in house prices and homeownership. in proceedings of the symposium "Housing, housing finance, and monetary policy." Kansas City: Federal Reserve Bank of Kansas City, 89–123.

Stewart, L. (2010). 2009 state residential mortgage foreclosure laws. NGA Center for Best Practices, available at: http://www.nga.org/Files/pdf /1001FORECLOSURELAWS2009.PDF.

USFN (2004). *The National Mortgage Servicer's Reference Directoty, 21st edition.* USFN:Tustin, CA.

Vita

Shuang Zhu was born in Beijing, China. She finished her undergraduate studies in mechanical engineering at Tsinghua University and earned a Master of Science in management science degree from Peking University. She obtained a Master of Art in mathematical finance from University of Southern California in 2003. She is a Chartered Financial Analyst (CFA) holder.

Her research interests include spatial econometrics, real estate finance, financial institutions and investments. She has publications in *Journal of Real Estate Finance and Economics* (forthcoming) and *Geographical Analysis*.

In August 2007 she came to Louisiana State University to pursue graduate studies in finance. She is currently a candidate for the degree of Doctor of Philosophy in finance, which will be awarded in August 2011.